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Localization and Detection of Targets in Underwater Wireless Sensor Using Distance and Angle Based Algorithms

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ABSTRACT Underwater localization is used as a key element in most applications of underwater communications. Despite the global positioning system (GPS) receivers are usually employed in terrestrial wireless sensor networks, they cannot be exploited for underwater localization. In fact, GPS signals are highly attenuated by the water, by being unusable to a depth of more than a couple of meters, and cannot propagate underwater, especially, in the case of the salt water. In place of RF signals, acoustic signals are the most common mode of communication, and the so-called underwater acoustic sensor networks attracted a significant interest due to their great impact on ocean monitoring and exploration. Hydroacoustics, as the study and application of sound in water, is the foundation of underwater localization, but the existing available methods, classified in range-based versus range-free techniques, are affected by several open problems and research challenges. Therefore, an accurate range-based algorithm for localization needs to be developed, and the demand for expeditiously employing the energy of the sensor nodes is still remaining a distinct feature for underwater wireless sensor networks. Because of these argues, an improved interpretation for underwater localization is presented, by first presenting a general localization algorithm, and afterward deploying the ordinary, beacon nodes in order to find the error and accuracy of sensor localization. After that, we present two localization algorithms named as distance-based and angle-based algorithms. We consider a realistic case, where sensor nodes are not time synchronized and the sound speed in water is unknown. The simulation results exhibit that our algorithms compensate for time synchronization, estimate the mean errors in localization and achieve good localization accuracy.

INDEX TERMS Wireless sensor networks (WSNs), underwater sensor networks (USNs), underwater acoustic sensor networks (UASNs), underwater localization.

I. INTRODUCTION

The underwater communications and technologies provide new opportunities for a more complete exploration of the oceans and the underwater environment in a variety of civilian and military applications. The recent advancement in sensor technology for underwater applications has led the way to the advent of the so-called Underwater Wireless Sensor Networks (UWSNs), where sensors are deployed underwater and leverage on a Distributed Antenna System (DAS) to get access to the terrestrial systems [1]. UWSNs are not only limited to the exploration purposes, but can also accomplish the demands of a multitude of underwater applications, which include collection of oceanographic data and natural disasters warning systems and support oil or mineral extraction, underwater pipelines or commercial fisheries. A general UWSNs architecture is shown in Figure 1, where the multitude of underwater sensors, deployed at different depths throughout the area of interest, can communicate among each other, but also with a set of sinks that interact with terrestrial systems

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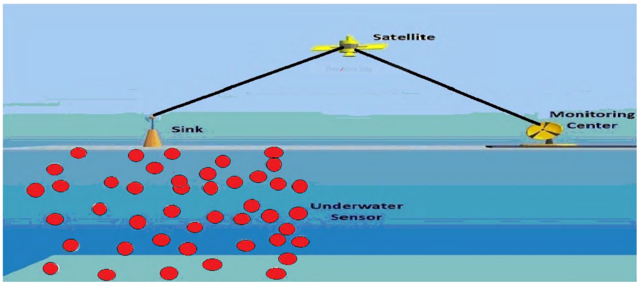

FIGURE 1. Architecture of underwater wireless sensor networks (UWSNs).

thanks to satellite communications. The sensor nodes can calculate some factors such as mooring tensions, quality of water, and foundation strength to control the structural health of the mooring system in deep water, biological monitoring, military underwater surveillance and so on.

As the proliferation of RF communication technologies promoted the advent and proliferation of terrestrial wireless sensor networks (TWSNs), these technologies and solutions cannot find a similar exploitation in the underwater context. In fact, in underwater RF communications, electromagnetic (EM) waves propagate over very short distances and exhibits a very high inter symbol interference (ISI), due to high levels of attenuation increased with sea state, temperature and salinity [2]. For these reasons, the terrestrial networking standards cannot be followed in underwater environments, and specific routing algorithms have been proposed over the year to cope with the peculiarities and the complicated application scenarios of these networks [3]. Specifically, acoustic communications impose themselves as the widely-recognized communication means for UWSNs, by making possible the effective design and implementation of these networks. The acoustic communications prove to guarantee a low data rate and high propagation delay, and the proper knowledge of the location information for underwater sensors is demanded to design network architecture and routing protocols. Due to the node mobility underwater, it is required for these protocols to keep up-to-date location information, periodically. Consequently, this causes an overhead of data and massive energy consumption. Like TWSNs, the sensor nodes are powered using batteries, but it is a complex task to replace or recharge the batteries in an underwater environment. Thus, to keep the availability of sensor nodes and increase the lifetime of the overall network, the energy efficiency is an extremely demanding aspect of any algorithm for UWSNs.

UWSNs work as a predominant technology for many applications, where various kinds of sensors and mobile vehicles are used, such as Unmanned Underwater Vehicles (UUVs), Autonomous Underwater Vehicles (AUVs), surface beacons and different ships [4], [5]. The organization and measurements of accurate locations are very important in this field. The design of management and network protocols is nearly interconnected with the network architecture [6]. Underwater localization is extremely important and crucial, because it is a basic building block for any other possible capability, such

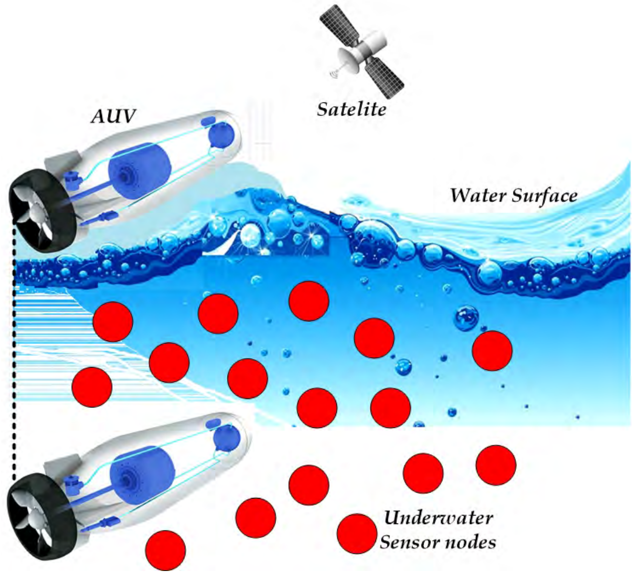

FIGURE 2. Localization using AUV-aided localization (AAL).

as tracking underwater nodes, tagging monitoring data, coordinating a group of nodes motion and detecting the position of underwater targets. Furthermore, information of a sensor node location can be utilized to optimize the routing and medium access protocols. Unfortunately, UASNs are characterized by a large delay in propagation, motion-stimulate Doppler shift, multipath interference, specific bandwidth, phase and fluctuations of amplitude [7], [8]. These properties introduce new obstacles and issues to cope with when designing any localization algorithms, aiming at accomplishing desired quality characteristics, such as fast coverage, wide coverage, high accuracy, low communication cost and good scalability. Because of the above issues, UASNs call for novel network, transport, architectures, localization and time synchronization solutions. Some of them have been presented in different previous works, as reviewed in [3], [4], [7]. In UWSNs, to find the location of a sensor node is important and the action of estimating the location of every sensor node in a WSN is called localization. Various localization techniques have been presented for TWSNs. Comparatively, there are few localization techniques for UWSNs. Fundamentally, the characteristics of UWSN are different from TWSN.

The AUV-Aided localization (AAL) scheme in [9] for a hybrid, 3D UASN where the nodes in underwater are standing and the AUV move in the UASNs region is shown in Figure 2. By using the dead-reckoning method, the AUV can be able to obtain its location underwater. The dead reckoning procedure is potentially viable by using the expensive inertial piloting equipment and the position has periodically updated. For that purpose, the AUVs is coming to the surface of the water to receive GPS coordinates from a satellite at specified time intervals. At first operation cycle of AUV, it can broadcast a wake-up message from a given point on its moving path.

Furthermore, AUVs leave an Omni-directional beacon [10] when AUV pass by a node at the time t_1. The corresponding

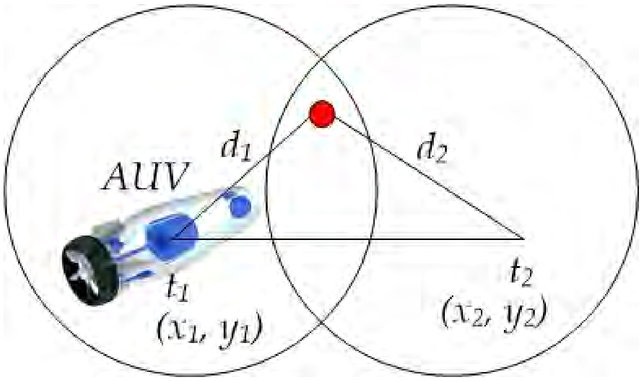

FIGURE 3. Omni-directional AUV-aided Localization.

node will receive a beacon message which is used for the calculation of distance d_1 between the sensor node and AUV. Similarly, at the time t_2, the distance d_2 can be estimated by TOA technique as shown in Figure 3. To achieve the location coordinates of the sensor node, the coordinates of the AUV at two different time instants are needed, allowing location to be estimated by means of a triangulation procedure. Furthermore, the AUV route is very difficult to analyze and predict, and to guarantee that each sensor node can obtain two mandatory beacon messages from AUVs.

Several industrial underwater navigation systems exist for self-localization, which are based on the direction and speed measurements. However, some of these algorithms present a reliable navigation property for small intervals in experimental settings. Whereas, in the case of long-time periods, these systems frequently get affected from lower accuracy because of the accumulated errors. For these reasons, the network localization algorithms are largely based on ranging techniques and underwater acoustic communications. The sensor node depth can be self-estimated, e.g., employing pressure probes. These types of localization techniques need ranging measurement to at least three reference nodes at a known position, such as anchor nodes [11]. Since acoustic waves are highly attenuated in water, the network topology useful for positioning purposes may be degraded. A network or sensor node that is trying to find its position may not be in the communication range of at least three anchor sensor nodes. Using acoustic waves, the direct field with acoustic energy density is similar to source acoustic energy density in the resound fields, and an open environment with an acoustic energy density such as W_r provided from the multiple walls reflections. The acoustic energy density of the direct field is depended on the distance r to the source [12] which is related by:

$$W_d(r) = (\frac{P_s}{4\pi cr^2}) \tag{1}$$

where P_s represents the source power and c is the velocity of sound. It presumes an omnidirectional source. The direct field depends on the direction if the source is directional. On the other hand, for the reverberated field, the reverberated medium is considered as isotropic and homogeneous in space. The acoustic energy density W_r and the acoustic intensity I_r for an isotropic homogeneous reverberated field are related by:

$$W_r = (\frac{4I_r}{c}) \tag{2}$$

Derivative with time of the total acoustic power in the tank, $Q = W_r(V)$, is the variance between the acoustic power which is compelled by source P_s and the acoustic power is degenerate by absorption on the wall.

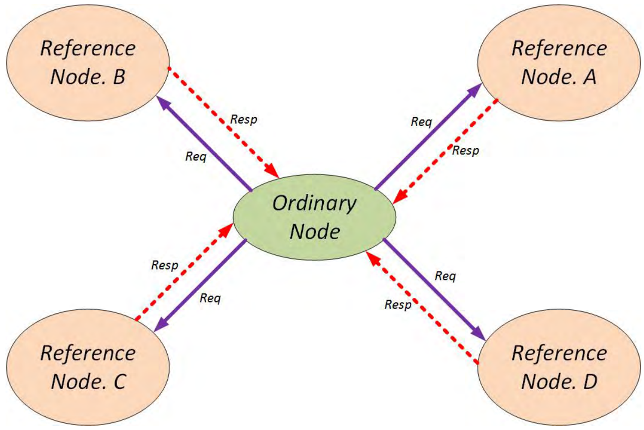

FIGURE 4. Two-way message exchange between ordinary and reference nodes.

UASN has limited bandwidth and characterized by the harsh physical condition of the underwater environment. Because of the long propagation delay and the variable speed of sound, underwater environment poses a distinctive set of challenges for localization procedure. In this work, we model some basic algorithms for underwater localization. First, we introduce a general localization of mobile and beacon sensor nodes where the sensor nodes transmit their data through beacons and then through the surface buoys antenna. After deployment of sensor nodes, we find the error in localization and estimate the accuracy of localization. Furthermore, we propose two new algorithms, namely distance and angle-based localization algorithms. We localize sensor nodes and estimate the mean estimation errors. Simulation results demonstrate the effectiveness of our proposed localization algorithms.

The remain of the paper is organized as follows. In Section II, we summarize related work. Present a general deployment of sensor nodes and beacons, distance based and angle-based localization algorithms in sections III, Section IV and section V, respectively. In Section VI, we present our simulation results. Finally, Section VII concludes this paper with some appropriate remarks.

II. RELATED WORK

In this section, we give a brief description of underwater localization. After that, we review some widely-known algorithms for the detection of targets under the water. Currently, most of the sensor nodes that are utilized for the oceanographic purposes are mostly localized either with Long Based-Line (LBL) or Short Base-Line (SBL) [13].

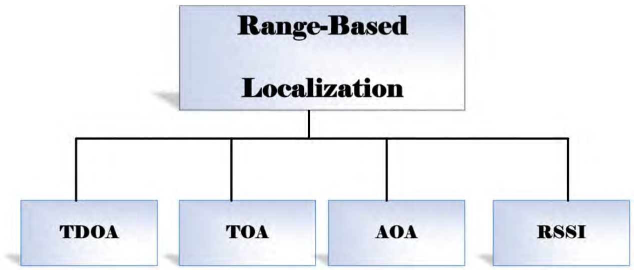

FIGURE 5. Range-based localization techniques (TDOA, TOA, AOA and RSS).

The position of sensors in both cases are estimated on the basis of acoustic communications with a set of receivers (Rx), with known positions. For the LBL system, acoustic antennas are equipped on both under the surface moorings or seafloor around the operation area. On the other hand, in SBL a ship is used to travel behind the sensor nodes and employ a short-range emitter source to perform the operation of localization. Furthermore, a commercial system for SBL localization utilizes a vessel for the localization of underwater equipments. For deployment of both algorithms, they required a long-term planning and up to somehow expensive.

Basically, there are two major categories of underwater acoustic localization, namely Range-based and Range-free. The range-based algorithm first estimates distances or angles to some anchor sensor nodes using TDOA, TOA, AOA and RSS as shown in Figure 5. Then, they apply multilateration or triangulation methods to convert ranges into different coordinates. On the other hand, the range-free algorithm inquires the local topology and the position estimate of sensor nodes that is estimated from the locations of the nearby anchor sensor nodes [14]. DOA estimation is an important part of the target parameter estimation which has found broad applications in sonar, radar and wireless communication. There have been a large number of DOA estimation algorithms in the past, which include Capon Minimum Variance Method (MVM), conventional beam forming, Multiple Signal Classification (MUSIC, Weighted Subspace Fitting (WSF) algorithm, Estimation of Signal Parameters via Rotational Invariance Techniques (ESPRIT), etc. Furthermore, in [15], the authors proposed a DOA estimation algorithm of underwater acoustic targets used for the micro underwater location platform. Authors search for a formulation of sensor array acoustic target localization problem in a sparse signal representation model. The scheme can be applied to narrow-band and wide-band scenarios. The DOA of a signal at a dumb node is used to measure its location. The received signal direction can be found by measuring the angle made with some reference direction. For the localization of a dumb node using this method, AOA from a minimum of three beacon nodes is estimated. Position information of three or more beacon nodes along with the three AOA can be used to measure the location of the dumb node. Using directional antennas, the AOA can be measured. These can be mounted on beacon sensor nodes when using directional antenna. Directional antenna mounted on a beacon sensor node rotating about its axis and broadcasting beacon signals in all directions.

TABLE 1. Underwater acoustic channels data rates with different ranges.

Span	Range (in km)	Data Rates (in kbps)
Short Range	<1	∼20kbps
Medium Range	1-10	∼10kbps
Long Range	10-100	∼1kbps
Basin Scale	3000	∼10kbps

The main objective of localization technique is to find the position of sensor nodes within the network of sensors (nodes with a known location) either relative or absolute with a fraction of the anchor nodes. Also, in [16], an energy efficient system for the detection and data collection of continuous objects is presented. Based on the techniques employed for position measurement, the localization algorithm is subdivided into two groups, range-based and range-free algorithms [17]. In range-based localization algorithms, the angle or distance is measured with neighboring sensor nodes for the estimation of node positions. Whereas, in range-free algorithms, the neighbor sensor node distance or information of angle is assumed to be not available for positioning because of the hardware and cost restrictions. One of the best endeavors of localization algorithms in UASN is presented by [18], in which it divides anchor sensor nodes at all network which utilize long-range acoustic channels to communicate with the buoys on the surface of the water. For shorter distance, the data rate of acoustic channels increases as seen in Table I. Basically, the Localization algorithm is divided into two sub-procedures, namely ordinary and anchor node localization. The ordinary sensor node receives messages from anchor sensor node in which anchor is communicating with the surface buoys. After that, ordinary node measures the distances to the surface buoys and thus localize themselves similar to the anchor nodes [19]. Therefore, the localization of an ordinary sensor node makes it unnecessary. Furthermore, researchers assume that the bearing of a large number of static sensor nodes which are deployed underwater. Some sensor nodes can achieve the ranging algorithm using the one-way exchange of messages and utilize synchronization of time which is really difficult to maintain in UASNs.

UASNs faces a unique set of challenges in the evolution of wireless communication and network protocols because of the unique characteristics of the underwater environment for the propagation of signals. For mobile sink architecture, to avoid multi-hop transmissions, a mobile sink that travels across the network to transport non-information without waiting from the sensors directly. An area partitioning technique splits the whole network into different areas to reduce the travel distance of the sink sensor node and the making of clumps that increase the output [20], [21]. A transmission algorithm which is based on the coding of superposition is presented to enlarge the output of down-link which command messages to the sensor nodes.

Underwater acoustic communication also has some disadvantages which are caused by the acoustic signals lower speed of propagation in underwater, which is around 1450 m/s. This type of slow propagation ineluctably enforces a constriction on the capacity of the channel for communication in underwater [22]. In underwater, the sound speed is changing with different causes such as temperature, depth and salinity which makes it difficult to accurately model and predict. Moreover, in underwater acoustic communication, the energy consumption is very high as compared to the terrestrial communication. However, the required transmission power for the receiver (Rx) is rather low, but the required power of transmission for the acoustic antennas might be large as around 50 watts.

In addition, due to the acoustic channel, rough underwater environment and their own distinctiveness, UWSNs are susceptible to attack and a wide class of security issues [23]. It is difficult to secure UWANs due to their distinctiveness, constraints and high cost of network maintenance and deployment. Also, the distinctiveness of UWANs imposes challenges and should be leveraged in the security schemes design. Moreover, the existent security mechanisms for WSNs cannot be directly employed in UWSNs. In [24], the authors present a novel algorithm named MAP-PSO which consist of two steps such as MAP estimation and PSO localization. For MAP estimation, they examine the patterns of node mobility; It supplies the anterior noesis for localization, and under the assumption of additive and multiplicative noises; It qualifies distance estimation which functions as the likelihood information for the localization process. Furthermore, the anterior and likelihood information is joined to obtain the localization objective function.

In [25]–[27], different techniques are applied such as a combined Time-of-Flight (TOF) and Direction-of-Arrival (DOA) localization approach which is suitable only for shallow water monitoring such as harbor monitoring. The localization provides localization and tracking of sound-source in short-range shallow water environments such as a harbor. The closest distance matching estimation algorithm and the horizontal distance estimation compensation algorithm are proposed. Furthermore, a multi-hop sensor nodes localization method in two-dimension (2D), which estimates Euclidean distances to different anchor nodes through multi-hop propagations by using the AOA estimation, is presented. However, this method encounters localization ambiguity. The aforementioned techniques provide the distance and AOA estimation, but they didn't measure the localization error and detection of targets underwater. Therefore, our proposed techniques provide a detailed measurement of localization error and provide a good level of accuracy.

III. LOCALIZATION OF ORDINARY AND BEACON NODES

To do localization in an underwater environment, due to the unavailability of resources, underwater network faces several problems in comparison with radio signals in terrestrial networks, especially delays in propagation is very large if the bandwidth is limited. Another limitation that required to be applied in UASNs is the lack of potential for the development of modems for the transmitting and receiving the signals at the same time. To solve the problem of near-far effect that causes data losses, a pre-planned transmission is needed. The node discovery algorithm must reduce the data exchange in order to keep networks lower degree management overheads. Moreover, in UASNs, the sensor node connectivity is unknown in advance. This issue of connectivity has faith upon many components such as noise level, a relative node orientation, fading and losses in propagation. By relative movement of sensor nodes, failure of sensor nodes and links, by the addition of new sensor nodes such type of connectivity, is foster affected.

The connectivity of networks can be developed for range measurement if there is no direct route of communication in between ordinary and anchor sensor nodes. Different localization algorithms are available such as DV-distance, DV-hop and Euclidean that are based on the connectivity of the network. However, Euclidean distance presents a good performance in the case of anisotropic topologies. For larger computation, there is a communication overhead and also expensive. A sensor node will be able to localize only if its position can be calculated uniquely. Otherwise, the sensor node is unable to localize. Although if a node is unable to localize, it may be still potential to measure many candidate locations [28]. Such kind of sensor nodes is localizable with a finite limit. In most of the localization algorithms, a to-be-localized sensor node localizes itself on the basis of some reference sensor nodes. Reference or sink sensor nodes are such types of nodes that have to achieve their information of position before the to-be-localized sensor node. In such a procedure, the beacons sensor node is used as an initial reference sensor node.

The consumption of energy should be minimized as much as possible for localization. At the same time, the accuracy of the localization algorithm is also required to be noticed. In [29], an approach is presented for underwater localization which is named as directional beacon-based approach UDB. Authors discuss and analyze the communication algorithm for UWSNs. With the accordance of the particular environment, they present a silent localization approach, which, in turn, makes all sensor nodes to discover their location themselves by calculating the geometric distances of passively received beacon nodes. To localize the ordinary and beacon nodes, we assume a specific number of nodes. For the first time, we deployed mobile sensor nodes randomly in an $80m \times 80m$ area, select 120 ordinary/mobile sensor nodes and 15 beacon nodes. The unknown number of sensor nodes are those when the beacon node amount is subtracted from the ordinary node amount. The random deployment of sensor nodes is shown in Figure 6, to find an error in the deployment and localization of sensor nodes:

$$E_{est} = \frac{\sum_{i=1}^{n}(E)}{\sum_{i=1}^{n}(UN)} \tag{3}$$

In equation (3), n is the number of nodes and the maximum number of nodes is 120. E is the error which is $E = E_1 + E_2 + \ldots + E_n$ and UN is the un-localized node amount.

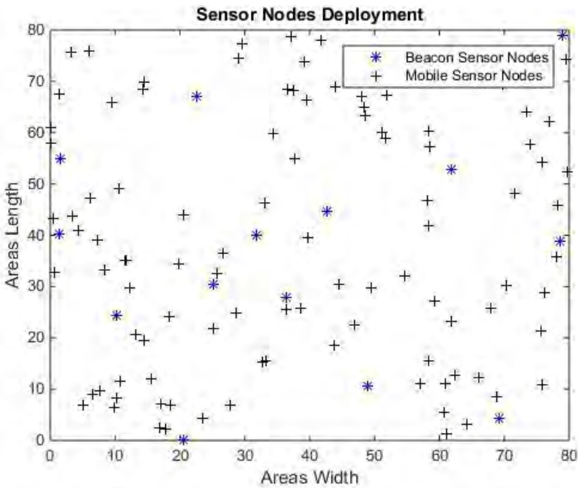

FIGURE 6. Deployment of sensor nodes.

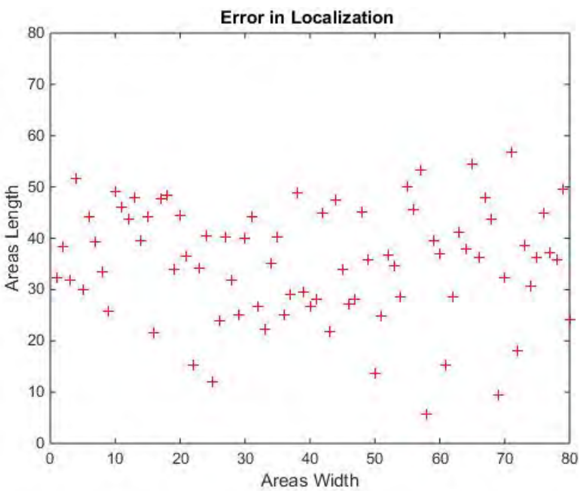

FIGURE 7. Error in localization.

The estimated average error is 29.76.

$$Accuracy = \frac{E_{est}}{R} \tag{4}$$

In equation (4), R is the range and the mean estimated accuracy is 0.5. The simulation results are shown in Figure 6 and Figure 7.

IV. DISTANCE-BASED LOCALIZATION ALGORITHM

For distance-based localization, estimation of the distance between any two sensor nodes is important which is mostly done by using range-based algorithms. Using a range-based localization algorithm, it can estimate the location of nodes by applying the information of distance in between the sensor nodes [30]. Distances between beacon nodes and the ordinary nodes are mostly measured by some additional hardware to the sensor nodes or sometimes using the existent source of radio communication. Most description of wireless communication is determined by the distance between the ordinary and beacon sensor node. If these properties are estimated at the receiving side of the sensor node, it can be utilized to measure the distance between the sensor nodes. For this purpose, most of these descriptions are used such as TDOA, TOA, AOA and RSSI.

Recent approaches can be found in [31] and [32]. The authors used smart phone-based distance-estimation only for indoor localization and achieve a distance error of 2.4% and a DV-Hop localization algorithm which is based on distance correction of anchor nodes which reduced the average localization up to 15% then the traditional localization, respectively. Similarly, in [33], a TDOA localization technique for shallow water in which a boat is equipped with two hydrophones and a communicating beacon is introduced. Another TDOA-based target localization technique is presented in [34], which measures the TDOA for the inhomogeneous underwater field. For the sake of brevity, we only focus on the recent localization works related to our method in order to judge the sensor node localization based on distance-based localization. In our proposed algorithms, we present a localization technique which estimates the mean estimation error in localization.

The algorithms of the proposed localization scheme are outlined as follows: select four anchor nodes and mobile nodes. Mobile nodes are deployed randomly in a $120m \times 120m$ region in which the mobile can roam and the anchor nodes are placed at the four vertices of the network region. Distance measurement error ratio is set to be 0.1. It means that the accuracy of distance measurement is 90 percent. For example, the inaccuracy of a $1m$ measured distance is around 0.1 meter. To find the mean estimation error, first we build a random location for the mobile sensor nodes. We set four iterations for the system. After setting the four iterations, we conclude that the mean estimation error is not static but in a dynamic mode as ranging from $4.8096m$ to $6.3613m$. Sometimes, the error jumps above $6.3613m$ by doing more iterations, but it is mostly ranging in between $4m$ and $6m$. The detail is available in simulation results.

To estimate the distance between the ordinary or mobile node and beacon node, the beacon is connected to the relative antenna. For this purpose, a Doppler speed measurement is applied in which it depends on both the mobile and beacon positions. Assume N is the number of total participating antenna nodes such as x_n, y_n, and z_n, where $n = 1, 2, 3 \ldots N$ and a vector such as [35]:

$$\Theta(k) = [x(k), \acute{x}(k), y(k), \acute{y}(k), z(k), \acute{z}(k)] \tag{5}$$

To presume a zero mean Gaussian additive noise for the active sensor node s at positions x_s, y_s and z_s is:

$$\Theta(k) = Arg_{\theta(k)} min \frac{1}{2(c\sigma_t)^2} \sum_{n=2}^{N} \times [c\delta\hat{t}_{n,1}(k) - (d_{sn}(k) - d_{s1}(k))]^2 + \frac{1}{\sigma_v^2} \sum_{n=1}^{N} \times \left(\hat{v}_n(k) - \sqrt{\acute{x(k)}^2 + \acute{y}(k)^2 + \acute{z}(k)^2} V_n(k)\right)^2 \tag{6}$$

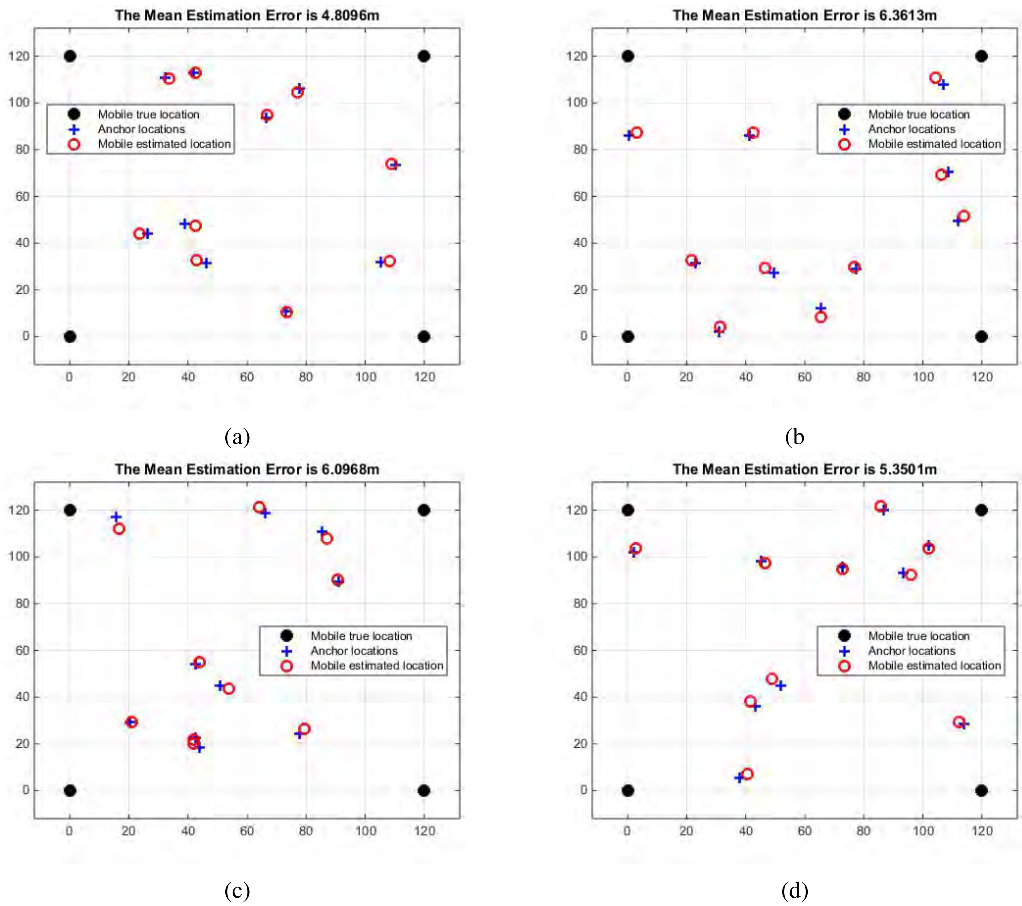

FIGURE 8. The mean estimation errors in Distance-Based localization at four different iterations. (a) Mean estimation error at iteration first. (b) Mean estimation error at iteration second. (c) Mean estimation error at iteration third. (d) Mean estimation error at iteration fourth.

Here $V_n(k)$ is:

$$V_n(k) = \left(\frac{x(k) - x_n}{r_n(k)} + \frac{y(k) - y_n}{r_n(k)} + \frac{z(k) - z_n}{r_n(k)} \right) \quad (7)$$

and $r_n(k)$ is:

$$r_n(k) = \sqrt{\left((x(k) - x_n)^2 + (y(k) - y_n)^2 + (z(k) - z_n)^2\right)} \quad (8)$$

Here σ_v represent the Doppler speed estimation error standard deviation, $v(k)$ is process noise, k is the time instant, τ is the sampling interval of the discrete model in seconds, and d_{sn} is the true distance from node s to node n,.

On the other hand, in case of two sensor nodes such as x_s, and y_s, the $r_n(k)$ will become:

$$r_n(k) = \sqrt{\left(x(k) - x_n)^2 + (y(k) - y_n)^2\right)} \quad (9)$$

Firstly, an initial sensor node is selected and then a gradient descent method is used to find the solution. Finally, the mean errors are estimated in simulation results, see Figure 8 and iteration results in Table II.

V. ANGLE-BASED LOCALIZATION ALGORITHM

AOA is basically defined as the angle between the incident wave propagation direction and some reference direction; it is known as an orientation. It is defined as a rigid direction opposed to which the AOA is estimated, and it is delineated through a degree in a specific direction of clockwise from the north side [36]. The AOA will be absolute if the orientation is 0^o or pointing to the North otherwise, it will be considered as relative or without orientation knowledge. In addition, the orientations of the unknown nodes may or may not be known at the time of deployment. The localizations under both outlines can be solved by using the technique of triangulation as shown in Figure 9. Using this technique, the location of an un-localized sensor node can be found by measuring the absolute or relative angles between the neighbor sensor nodes.

In [37], the authors present a range-angle based self-localization for Mobile Underwater Acoustic Networks (MUANs). In this technique, each mobile sensor node can

TABLE 2. The Distance-based localization mean estimation errors.

Iterations	Mean Estimation Errors (in meters)
Iteration 1	4.8096 m
Iteration 2	6.3613 m
Iteration 3	6.0968 m
Iteration 4	5.3501 m

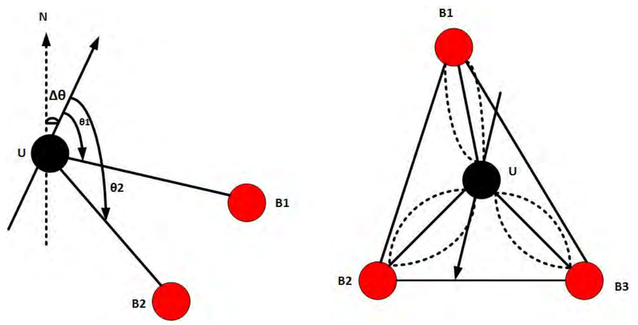

FIGURE 9. Angle-based localization.

only communicate with the anchor sensor node which sends localization message and mobility model to the network. Also in [38], a simple AOA-based localization technique is presented which estimates the distance from the sensor to anchor node through multi-hop by using AOA measurement. When a sensor node collects distance measurement from at least three or from four anchors, the location of the sensor node is calculated. Similarly, in [39] a probabilistic estimation of multi-target localization is presented which use the frequency bands to identify the target acoustic signals, but only a rough localization of the multi-sensor is done with no error estimation. In the recent research, different algorithms are presented, but still need some improvement for localization.

Therefore, we present a new localization algorithm based on angle for the purpose of achieving a good accuracy. The algorithm of the proposed localization scheme is outlined as follows: We build a random location for the mobile node, and then we compute the Euclidian distances. At the initial guess, a random location is calculated and the estimated distances is computed. After computing the derivatives, root mean square error is computed. Here for the case, we consider 4 anchor nodes, 10 mobile sensor nodes and the overall network area is $80m \times 80m$. The angle measurement ratio is considered as 0.1; It means that the accuracy of distance estimation is 90. For example, the inaccuracy of a $1m$ estimated distance is around 0.1 meter. We consider nodes A and B at positions X_1, Y_1, X_2 and Y_2 such as:

$$A_\circ = \sqrt{X_1 + Y_1} \tag{10}$$

and

$$B_\circ = \sqrt{X_2 + Y_2} \tag{11}$$

To find distance between these nodes:

$$AB = \sqrt{(X_1 - X_2)^2 + (Y_1 - Y_2)^2} \tag{12}$$

For estimation of angles between nodes such as:

$$\cos\theta = \frac{A_\circ + B_\circ - (AB)^2}{2A_\circ B_\circ} \tag{13}$$

The extended form above equation can be rewritten as:

$$\cos\theta = \frac{X_1X_2 + Y_1Y_2}{\sqrt{X_1^2 + Y_1^2}\sqrt{X_2^2 + Y_2^2}} \tag{14}$$

TABLE 3. The angle-based localization mean estimation errors.

Iterations	Mean Estimation Errors (in meters)
Iteration 1	114.1541 m
Iteration 2	114.4581 m
Iteration 3	114.6485 m
Iteration 4	115.2272 m

TABLE 4. The simulation parameters.

Parameters	Values
Border length (m)	80
Node amount	120
Beacon nodes	15
No. of anchor nodes	4
No. of mobile nodes	10
Distance-based Network size (m)	120 × 120
Angle-based Network size (m)	80 × 80
Distance measurement error ratio	0.1
No. of iteration	5 ∼ 10

Furthermore,

$$\theta = \cos^{-1}\left[\frac{X_1X_2 + Y_1Y_2}{\sqrt{X_1^2 + Y_1^2}\sqrt{X_2^2 + Y_2^2}}\right] \tag{15}$$

Therefore, we measure the angles between sensor nodes and finally find the mean estimation error of localization through simulation. The simulation results are available in Figure 10. and the iteration results in Table 3.

VI. SIMULATION RESULTS

In this section, we assess the performance of different localization algorithms using simulations. The simulation parameters are shown in Table 4.

A. SIMULATION SETTINGS

In these simulations, basically, we consider the two major cases such as general localization of ordinary/mobile sensor nodes and beacon sensor nodes and then we localize sensor nodes for the detection of single/multiple targets using the two algorithms, namely distance-based localization and angle-based localization algorithms. For the first case, we considered 120 mobile sensor nodes which are randomly distributed in an $80\,m \times 80\,m$ region. For the second two cases, we considered 10 mobile sensor nodes which are haphazardly distributed in an $120\ m \times 120\ m$ and $80\ m \times 80\ m$ region, respectively. The node density is defined as the expected number of sensor nodes in a nodes neighborhood. Therefore, the density of every sensor node is similar to the degree of the sensor node. Furthermore, we manage the density of nodes defined as the expected number of nodes by varying the range of communication for every sensor node while keeping the deployment area similar. The estimation of the distance between sensor nodes is considered to comply with the normal distributions with real distances like the intended values. Besides distance-based localization, a localization scheme of mobile nodes using underwater distributed antennas is presented above in [20] for comparison. Also, in [40], a novel

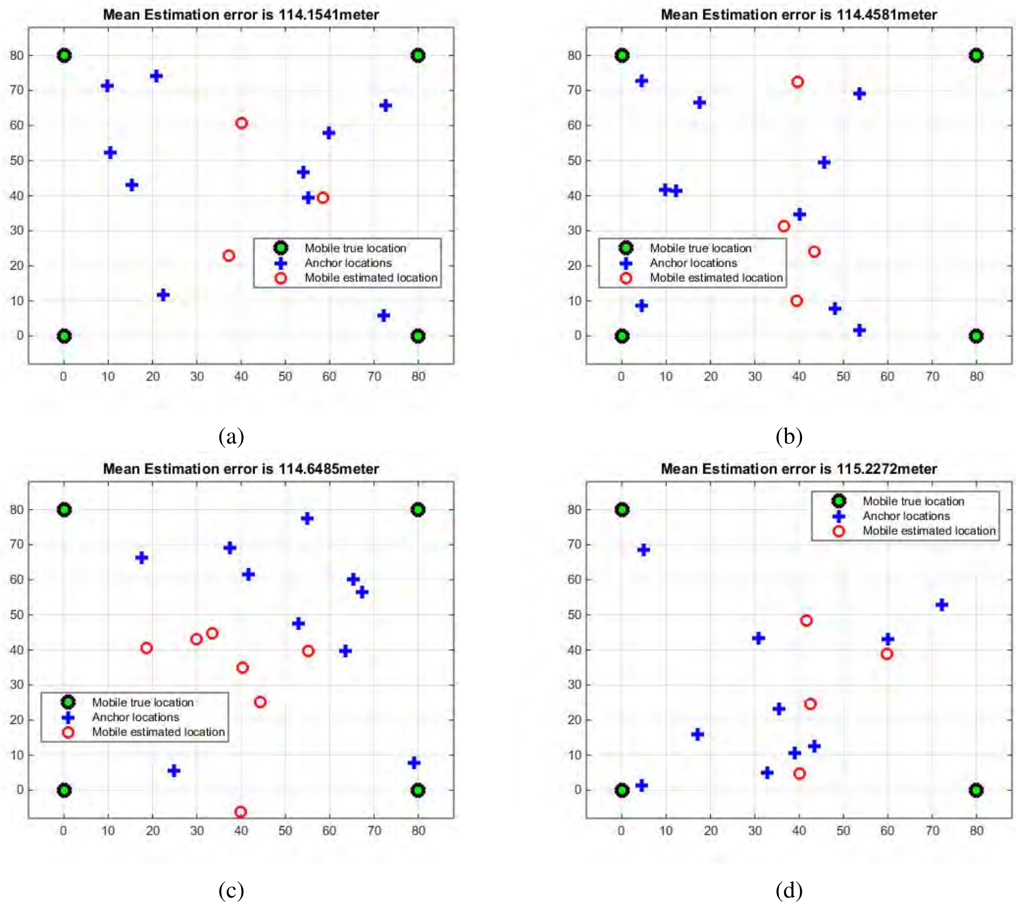

FIGURE 10. The mean estimation errors in Angle-Based localization at four different iterations. (a) Mean estimation error at iteration first. (b) Mean estimation error at iteration second. (c) Mean estimation error at iteration third. (d) Mean estimation error at iteration fourth.

underwater sensor network localization approach is presented which is based on distance transform-based skeleton extraction. In this approach, the efficiency rate of sensor localization keeps high and steady in most cases, but at the same time, the extracted skeleton is robust to the noise boundary.

In our simulation three performance metrics are weighed, such as coverage of the localization process, error in localization and the cost of communication averagely. Coverage of localization can be defined as the relative magnitudes of the localizable sensor nodes to the total number of sensor nodes. An error of localization is basically the distance average between the real location of all nodes and the estimated location of nodes. The communication cost is defined as the total exchanged of messages between sensor nodes in the network divided by the number of sensor nodes which are localized.

B. ANALYSIS AND RESULTS

1) LOCALIZATION PERFORMANCE OF MOBILE AND BEACON NODES

For the performance of mobile/ordinary sensor nodes and beacon, the simulation is set to be as we select 120 mobile sensor nodes and 15 beacon nodes randomly with an $80m \times 80m$ border length. First, we generally deploy the sensor nodes randomly at the whole network area as shown in Figure 6, then we estimate the localization error as shown in Figure 7. The average error is 29.76 which is the sum of all errors divide by the unknown nodes amount and the mean estimated accuracy is estimated through the average error divided by the total range. So, the accuracy estimated is 0.5.

2) PERFORMANCE WITH DISTANCE-BASED LOCALIZATION

In this set of simulations, we select 10 numbers of mobile sensor nodes, 4 anchor nodes which are deployed randomly in a $120m \times 120m$ network region in which the mobile can roam. For the whole network, the distance measurement error ratio is set to be 0.1. It means that the accuracy of distance estimation is 90. For example, the inaccuracy of a $1m$ estimated distance is around 0.1 meter. To find the mean estimation error first, we build a random location for the mobile sensor nodes. We set four iterations for the system. After the four iterations, we conclude that the mean estimation error is not static but in a dynamic mode as ranging from 4.8096 m to 6.3613 m. Sometimes, the error jumps above 6.3613 m by

TABLE 5. Comparison table of distance-based and angle-based algorithms.

Iterations	Distance-based	Angle-based
Iteration 1	4.8096 m	114.1541 m
Iteration 2	6.3613 m	114.4581 m
Iteration 3	6.0968 m	114.6485 m
Iteration 4	5.3501 m	115.2272 m

doing more iterations, but mostly in between 4 *m* and 6 *m*. Basically, the changing of mean estimation error is due to the dynamic motion of mobile nodes in underwater because of the water current and shipping activities. All the four iteration results are shown in Table 2, and the mean estimation errors are shown in Figure 8(a-d).

3) PERFORMANCE WITH ANGLE-BASED LOCALIZATION

In this part of simulations, the number of mobile sensor nodes and beacon nodes is similar to the distance-based localization algorithm. Here $80m \times 80m$ is the network region in which the mobile can roam. For the whole network, the distance measurement error ratio is set to be 0.1. It means that the accuracy of distance measurement is 90. For instance, the inaccuracy of a $1m$ measured distance is around 0.1 meter. For this scenario, we firstly find the distance between two sensor nodes and then estimate the angles between them. Resultantly, the mean estimation error in angle-based localization is greater than the distance-based localization. The estimation error in case of angle-based localization is ranging from 114.1541 *m* to 115.2272 *m*. In this case, the error is also dynamic due to the water current and mobility of sensor nodes. The process is repeated up to four iterations, all the four iteration results are available in Table 3, and the mean estimation errors are shown in Figure 10(a-d).

C. COMPARISON

After simulating all the algorithms and to compare them with each other, the average error was measured as 29.76 which indicates that the accuracy is of 0.5 as shown in Figure 6 and Figure 7. After that, we simulate the two algorithms (distance and angle-based localization algorithms). In the distance-based algorithm, the mean estimation error is too low, but the mean estimation error in the angle-based algorithm is high as shown in Table 5. Therefore, the communication overhead and cost of the distance-based algorithm is much lower in comparison with the angle-based algorithm. So, distance-based algorithm is more efficient and reliable. One drawback in both the cases and especially for the angle-based algorithm is the dynamical motion and mobility of nodes due to the water current and shipping activities. By increasing the network area of the angle-based algorithm from 80 *m* to 120 *m*, we checked the error. Consequently, the mean estimation error also increases. On the other hand, by increasing the distance measurement error ratio in distance-based algorithm, it tends to increase the error, but in angle-based algorithm it does not show any increment in the error.

VII. CONCLUSION AND SUGGESTIONS

In this paper, we introduce a general localization of ordinary/mobile sensor nodes and beacon nodes where the sensor nodes transmit their data through beacons and then through the surface buoys antenna. Although all the sensor nodes are deployed randomly and their x and y coordinates cannot be arranged, the sensor nodes can be lowered at any depth of water. After the deployment of sensor nodes, we find that there is an error in localization and the estimate of the accuracy of localization.

Furthermore, we introduce two new algorithms for localization, namely distance-based and angle-based localization algorithms. In both algorithms, we applied many iterations; At every iteration, the mean estimation error is dynamically changing. However, we select only four iteration results because the mean estimation error mostly varies within these iterations as shown in Figure 8 and Table 2. The mean estimation error of the distance-based algorithm is ranging from $4m$ to $6m$ and sometimes up to $7m$. On the other hand, the mean estimation error of the angle-based algorithm is higher than distance-based algorithm, which is ranging from $114m$ to $115m$ and sometimes up to $116m$. Similarly, we select only the four iteration results as shown in Figure 10 and Table 3. We presented performance evaluation results of distance-based and angle-based algorithms in terms of localization efficiency, error and cost of communication.

In summary, each one of these algorithms presents a different level of accuracy of estimated positions and it is directly relating to the number of anchor sensor nodes deployed in the sensor network. A good level of accuracy can be obtained if a higher number of beacon nodes are deployed in the underwater field. The comparison, cost and efficiency of both algorithms are explained in detail in the above section. For future work, regarding the proposed distance-based and angle-based localization algorithms, we will work on it to apply them into space of dimension $d > 2$. We will also work on the dynamic nature of sensor nodes to reduce the localization estimation error more and more.

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